4. Multivariate analyses of well-being outcomes

Modeling considerations. As we have already discussed, each of the well-being outcomes that we examine is measured using a series of related indicators. For our multivariate analyses of these outcomes, we must consider whether and how best to combine the information from the individual items. There are several things to consider. On the one hand, we may be able to improve the precision of the estimated relationships between the explanatory variables and the outcome variables by combining items. On the other hand, we may lose some information associated with the individual items if we combine them. Also, estimation results may be sensitive to the way in which we combine the items. With these considerations in mind, we conduct several types of multivariate analyses.

Single-equation specifications. One general multivariate approach is to apply standard single-equation statistical techniques to the summary measures that we have already constructed. For instance, to examine food hardships, we can use the food security scale described by Nord et al. (1999) as an outcome measure and estimate an ordered categorical model, like the ordered probit model, of whether households were food secure, food insecure without hunger and food insecure with hunger. Similarly, we could use the count measures of food hardships or other adverse events and model these with either an ordered categorical procedure or a simple regression procedure. The main advantages of the single-equation approach are that it combines information from the underlying items and that it is easy to apply. The disadvantages are that the approach relies on particular specifications of the outcome variables and that it may impose an inappropriate scaling on the outcomes.

Multiple-equation specifications. As our preferred statistical approach, we develop and estimate multiple-equation specifications for our three general well-being outcomes that jointly model (a) the behavioral processes relating the explanatory variables to a summary index measure of well-being and (b) the measurement processes relating each of the individual well-being items to the same index measure.

Behavioral model. Consider the model for food hardships. Suppose there is an underlying index for food hardships that depends on a set of observed variables, X_i, and a normally distributed unobserved variable, ε_i, with mean zero and variance σ_ε^2 such that

$$f_i^* = \beta X_i + \varepsilon_i \quad \text{where } \varepsilon_i \sim N(0, \sigma_\varepsilon^2).$$

This type of index specification is commonly used in single-equation binary models, like probit and logit models. The index implies that there is a continuous underlying distribution of food hardships.

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Measurement model. Suppose also that people's responses to each of the six discrete-outcome food security questions depend on the underlying index, a fixed threshold, δ_j, and a normally distributed random component, ν_{ji}, as follows:

$$
\begin{array}{lll}
q_{1i}^* = f_i^* + \nu_{1i} & Q_{1i} = 1 \text{ if } q_{1i}^* > 0, & = 0 \text{ otherwise} \\
q_{2i}^* = \lambda_2 f_i^* + \nu_{2i} & Q_{2i} = 1 \text{ if } q_{2i}^* > \delta_2, & = 0 \text{ otherwise} \\
q_{34i}^* = \lambda_{34} f_i^* + \nu_{34i} & Q_{3i} = 1 \text{ if } q_{34i}^* > \delta_3, & = 0 \text{ otherwise} \\
 & Q_{4i} = 1 \text{ if } q_{34i}^* > \delta_4, & = 0 \text{ otherwise} \\
q_{5i}^* = \lambda_5 f_i^* + \nu_{5i} & Q_{5i} = 1 \text{ if } q_{5i}^* > \delta_5, & = 0 \text{ otherwise} \\
q_{6i}^* = \lambda_6 f_i^* + \nu_{6i} & Q_{6i} = 1 \text{ if } q_{6i}^* > \delta_6, & = 0 \text{ otherwise}
\end{array}
$$

where $\nu_{ji} \sim N(0, 1)$, $\text{Cov}(\varepsilon_i, \nu_{ji}) = 0$, and $\text{Cov}(\nu_{ji}, \nu_{ki}) = 0$ for $j, k = 1, 2, 3, 5, 6$ and $j \neq k$. Higher values of the continuous index, f_i^*, increase the chances that a household will report a given problem. The thresholds for reporting specific problems—indicators of the severity of the problems—vary across the six items. The strength or relevance of the underlying index for a given problem also varies across items, depending on the size of the λ coefficient.

The specification is a variant of the Multiple Indicator Multiple Cause model that was developed by Jöreskog and Goldberger (1975). The main difference between their original specification and this one is that this one uses discrete-valued indicators, rather than continuous indicators, as the outcome measures. The model is diagrammed in Figure 2.

The model is implemented in the aML software package by specifying a system of four bivariate probit models and one ordered probit model that share a common random effect, ε_i. The relevant program code is shown in Appendix B. The aML package jointly estimates values for the index coefficients β, the index random variance σ_ε^2, the response thresholds δ_2, δ_3, δ_4, δ_5 and δ_6, and the response loadings λ_2, λ_{34}, λ_5 and λ_6 using maximum likelihood and applying the numerical quadrature technique of Butler and Moffitt (1982) to integrate out the common random effect.[3] Similar models are specified for other adverse events and for the changes in subjective assessments of well-being.

As with the single-equation specification, the MIMIC model combines all of the information from the different indicators. However, it has several advantages relative to the single-equation specification. First, instead of imposing an ad hoc scaling on the well-being index, the multiple-equation specification allows the scaling to be determined as part of the measurement component of the model in the estimation process. Second, the procedure allows for differences in the amount of random variance or response error associated with each item in the measurement component of the model. This is done through the λ parameters, which are inversely related to the amount of item-specific variance. Third, although the model is written in terms of a single index, there are several ways to extend the model to allow multiple indices. Thus, we can easily test the single-index restriction of the model.

[3] There are other ways to estimate MIMIC models for categorical data. Maddala and Trost (1981) developed a maximum likelihood estimator with a more general covariance structure between categorical indicators but that only considered three indicators. Browne and Arminger (1995) review other estimation methods, including a multi-stage marginal likelihood and minimum distance method.

The main disadvantage of the model is its complexity. Special software and procedures are needed to estimate the model. Also, it is difficult to interpret the coefficient estimates because of the non-linear specification and the use of multiple indicators. The coefficients can tell us whether a change in an explanatory variable is positively or negatively associated with the index. However, without additional computations, we cannot tell what the magnitude of the association is in relation to the probability of reporting a particular problem or in relation to the summary measures, such as the food security scale.

An alternative, related estimation approach with many of the advantages of the MIMIC model is the Rasch model (see, e.g., Wilde and Nord 2005). The Rasch model, which was used by the researchers who developed USDA's food security scale, is similar to the MIMIC model in that it relates multiple discrete outcomes to a single latent index. The Rasch model differs, however, in assuming that the unobserved determinants of the responses follow a logistic distribution rather than a normal distribution. The Rasch model is also more restrictive because it does not allow for differences in the response loadings. This restriction greatly simplifies the computation of the model; however, it effectively sets the amount of item-specific variation to be equal across outcomes. Initial tests of our MIMIC specifications rejected this equal-variance restriction for all three domains of well-being outcomes.

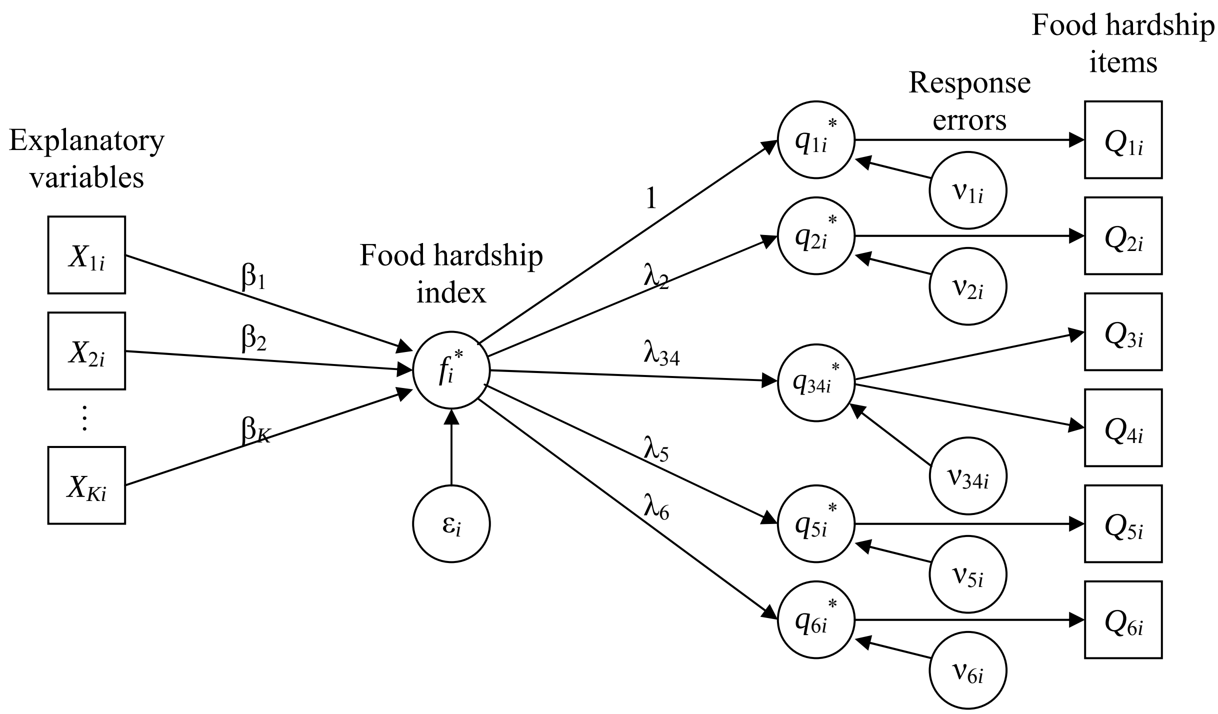
Estimation results. Food hardships. Table 3 lists coefficient estimates and standard errors from three multivariate models of the determinants of food problems. The first column of Table 3 reports results from an OLS model in which the dependent variable is a count (from 0 to 6) of the affirmative responses to the food security questions. The second column lists results from an ordered probit model of the food security scale (0 = food secure, 1 = food insecure without hunger evident, and 2 = food insecure with hunger evident), while the final column reports estimates from the MIMIC model of food hardships. Explanatory variables are listed along the left-hand side of the table. All of the models incorporate the same explanatory variables, and the results are very similar across specifications.

In each of the models, food hardships are estimated to have a negative association with total monthly non-assistance income. Although the associations are statistically distinguishable from zero, they are not especially strong. For instance, in the OLS model a change in monthly income from the bottom of our scale ($0) to the top of our scale (over $2,000) is associated with just one less affirmative food hardship response. Refusing or not being able to report an income amount is also negatively associated with reporting food hardships. The size of the association is comparable to that of changing the monthly income from $0 to $2,000. The results for missing incomes may reflect well-off families being less likely to report their incomes; they could also reflect a general reluctance by some people to report information about their well-being.[4]

Food stamp participation in the twelve months before the interview is positively associated with food problems. The coefficient is statistically significant in the OLS and ordered probit models and falls just short of being significant in the MIMIC model. The size of the association is not particularly large—participating in food stamps for an entire year is estimated

[4] The data from the survey do not indicate that there are missing values for any of the food security, adverse event, or subjective assessment questions. The total absence of item non-response in these variables is suspicious. The interviewers or coders may have included refusals and "don't knows" with the negative responses.

Figure 2. Diagram of Food Hardship MIMIC Model



to increase the number of affirmative responses by about one. The positive association likely reflects greater need among the households that received food stamps rather than an adverse effect of the food stamps themselves. Similar associations appear in descriptive analyses of these outcomes (see, e.g., Nord et al. 2002) and multivariate analyses that do not account for the endogeneity of food stamp receipt (see, e.g., Gundersen and Oliveira 2001; Ribar and Hamrick 2003).[5]

Food hardships also appear to increase with the age of the family respondent. The associations are statistically significant in the OLS and MIMIC models but not significant in the ordered probit model. None of the other explanatory variables has a statistically significant association with food hardships in any of the models.

Coefficient estimates for the threshold parameters, $\delta_2 - \delta_6$, in the MIMIC model give us one more way to assess people's food hardship reporting behavior. The six food security questions are intended to capture increasingly severe hardships, with the anticipated ordering being Q1-Q2-Q3-Q5-Q4-Q6 (Bickel et al. 2000).[6] When we examine the estimates, we see that this exact ordering is maintained, which provides evidence that respondents answered the food hardship questions in a reasonable way.

The bottom of the third column of Table 3 lists other coefficients from the MIMIC model. The parameters $\lambda_2 - \lambda_6$ are weights or loadings of the common latent index for answering questions $Q_2 - Q_6$ (the weight for Q_1 is normalized to one). The inverses of these parameters indicate the amount of the residual item-specific response variation for each of the questions (low values of λ indicate that there is a high level of item-specific response variation, while high values indicate a low level of variation). All of the λ coefficients are less than one; λ_{34} is significantly so. Thus, the residual item-specific variation is estimated to be lowest for question Q_1, which covers food not lasting and not being able to purchase more. For each of the questions, only about one-quarter to one-third of the unexplained variance is unique to the question itself; the rest is attributable to the component ε that is shared across questions.

An important issue that arises for the food security scale and for our multiple equation model is whether a single latent index is appropriate or whether multiple indices better describe the data (see, e.g., Johnson 2004; National Research Council 2005). A straightforward way to test for this is to respecify the thresholds ($\delta_2 - \delta_6$) so that they are linear functions of all of the observed variables in the latent index (e.g., let $\delta_2 = \Delta_2 X_i$). We did this to each of the thresholds and compared the fit of the resulting models to the model in Table 3. Based on likelihood ratio tests, we could not reject the single index specification.

<u>Other adverse events</u>. Table 4 lists results from three multivariate models of the determinants of non-TANF food stamp leavers experiencing other adverse events. The first

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[5] We experimented with 2SLS specifications to address the endogeneity of food stamp participation. However, we were unable to find instruments that could adequately predict food stamp receipt in the first stage of the procedure. Without predictive instruments, the 2SLS method is unreliable, so we do not report results from these specifications.
[6] The numbers for the questions (Q1, Q2, etc.) indicate the actual order in which they are asked in the survey. Even though question Q4 indicates a more severe condition than question Q5, it is asked earlier because it is a natural follow-up to question Q3.

Table 3. Multivariate Models of Food Hardships

	OLS model of count of problems	Ord. probit model of food insecurity	MIMIC model
Explanatory variables			
Age	0.0184*	0.0089	0.0222*
	(0.0108)	(0.0071)	(0.0117)
Male	-0.2619	-0.1709	-0.3765
	(0.2412)	(0.1583)	(0.2552)
Black	-0.2057	-0.1160	-0.1477
	(0.1551)	(0.0983)	(0.1642)
Completed high school	-0.1730	-0.1131	-0.2423
	(0.1656)	(0.1081)	(0.1785)
Second year of survey	-0.0544	-0.0533	-0.1582
	(0.1520)	(0.1001)	(0.1688)
Number of preschool age children	0.1531	0.0736	0.1338
	(0.1254)	(0.0823)	(0.1394)
Number of school age children	0.0001	0.0012	0.0086
	(0.0730)	(0.0500)	(0.0846)
Number of other adults	0.0836	0.0705	0.0268
	(0.1298)	(0.0791)	(0.1374)
Two-parent household	-0.1090	-0.0469	-0.1073
	(0.1627)	(0.1031)	(0.1724)
Total monthly income	-0.1391**	-0.0686*	-0.1528**
	(0.0623)	(0.0411)	(0.0703)
Income missing	-0.9496***	-0.4892**	-1.0823***
	(0.3156)	(0.2138)	(0.4044)
UI earnings 13-24 months ago	0.0132	0.0072	0.0153
	(0.0118)	(0.0077)	(0.0130)
FS participation in last year	0.9104**	0.5260*	0.8018
	(0.4495)	(0.2802)	(0.5002)
FS participation 13-24 months ago	-0.2641	-0.1676	-0.3223
	(0.2392)	(0.1567)	(0.2560)
Intercept, thresholds and loadings			
Intercept	2.1835***	0.1271	0.6790
	(0.6315)	(0.3435)	(0.5573)
τ_2		1.1683***	
		(0.0658)	
δ_2			0.6801***
			(0.1252)
δ_3			1.2246***

			(0.1172)
δ_4			1.5164***
			(0.1259)
δ_5			1.4776***
			(0.1490)
δ_6			2.8659***
			(0.5320)
λ_2			0.8919***
			(0.1624)
λ_{34}			0.6372***
			(0.1083)
λ_5			0.8185***
			(0.1474)
λ_6			0.9050***
			(0.2474)
σ_ε			1.6195***
			(0.2096)
R^2; log likelihood	0.040	-621.40	-1597.47

Note: Models estimated using a survey of former food stamp families in South Carolina (Richardson et al. 2003). Estimated standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.

column in the table lists coefficient estimates and standard errors from a probit model of the binary outcome of experiencing any adverse events. The second column lists results from an OLS model of the count (from 0 to 9) of adverse events, while the third column reports results from a MIMIC model of adverse events. The models include the same explanatory variables as the food hardship models in the previous table.

As with the food hardship results, the estimates from Table 4 indicate that households are less likely to report adverse events and report fewer events if they have high incomes or if they did not report an income. The coefficients on the income amount variable are statistically significant in all three specifications, and the coefficients on the missing income indicator are significant in two specifications. In the OLS model, each additional $1,000 in reported monthly income reduces the number of adverse events by roughly 0.4. Also like the food hardship results, participation in the Food Stamp Program is positively associated with adverse events; the coefficients are statistically significant in all three specifications. Again, it is difficult to give a causal interpretation to the participation results; the associations most likely reflect greater need among food stamp recipients.

Several significant associations appear in the models for adverse events that did not appear in the models for food hardships. One of these is a negative association for high school completion. More education may directly improve people's abilities to navigate difficult situations and avoid adverse outcomes. Education may also lead to higher permanent incomes and more stable employment and incomes, which would also contribute to fewer adverse events. Significant associations are also estimated for UI earnings from the year before leaving the Food Stamp Program. Earnings in this period are positively associated with reporting adverse events. The result is somewhat counter-intuitive because we expect that higher earnings would be associated with more resources, which should reduce the number of adverse events. However, higher earnings in earlier periods may have also led people to adjust their standard of living upward, causing them to perceive or actually experience more problems later.

One other difference in the multivariate models of adverse events and food hardships is that age is not a significant determinant of adverse events. The coefficients on age are all positive in Table 4, but they are not significantly different from zero.

For the MIMIC model, the events were not ordered by severity, so we observe both positive and negative estimates of the threshold values. The reporting thresholds for falling behind in rent (A2), falling behind in utilities (A3), going without electricity (A4), going without heat (A5), and losing telephone service (A7) are all significantly negative, indicating that these hardships are more likely to be reported than the reference event of having to move (A1). The estimated thresholds for reporting that a car or truck was taken away (A8) and that the household could not get needed medical care (A9) are positive, indicating that these hardships may be less likely to be reported than having to move; however, the estimates are not significantly greater than zero. When we examine the λ terms, there appears to be significantly less item-specific variation associated with reporting losses of electricity and heat and significantly more variation associated with reporting problems getting medical care than with reporting having to move. Reports of all of the other adverse events have roughly the same item-specific variation as the reference problem of having to move—the λ parameters for these events are all statistically indistinguishable from one.

Changes in subjective assessments of well-being. Table 5 lists results from multivariate models of the determinants of the parents in food stamp leaver families adopting more negative assessments of their life circumstances. For these outcomes, we were initially less sure that the responses could be categorized by a single latent variable. Also, because there are only three outcomes to consider, we could be more flexible in the type of models that we estimated. Accordingly, we decided to fit a system of correlated probit models for the three subjective assessment outcomes. The system includes separate models and, hence, separate indices for each outcome. It also allows for an unrestricted set of correlations among the unobserved determinants. Thus, the specification represents an unrestricted mean and covariance structure for the set of outcomes. The coefficient estimates and standard errors from the models in this system are reported in the first three columns of Table 5. We also estimated a MIMIC model for the changes in subjective assessments, which imposed a single-index restriction on the mean and covariance structure. Results from the MIMIC specification are reported in the last column of Table 5. A comparison of results from the two specifications helps to illustrate some of the trade-offs associated with the single- and multiple-index modeling approaches.

In the models for the specific outcomes and in the MIMIC model, the categorical variable for the family's monthly income amount and the indicator for not reporting an income are estimated to be significantly negatively associated with forming more negative assessments. The results are similar to those for food hardships and other adverse events and indicate that concerns and worries grew more among parents with fewer resources.

The number of preschool-age children is estimated to be associated with parents assessing their situation more negatively. The coefficients are significant in the individual equation for parents feeling worse about the previous year's changes and in the MIMIC specification. The results demonstrate one of the advantages of the MIMIC approach. By combining information from the three outcomes, the MIMIC model produces a more precise estimate of the relationship between small children and subjective assessments. In this case, the *p*-values of the coefficients from the individual models for feeling worse, worrying more, and feeling more stress are .07, .10 and .11, respectively, while the *p*-value for the coefficient from the MIMIC model is .04. The improvement in precision is reflected in the reduction in the estimated standard error in the MIMIC model, which is only one-half as large as the corresponding standard error from the individual model for feeling worse.[7]

There are several possible explanations for the association between small children and changes in assessments. In particular, we hypothesize that families with small children have larger financial and consumption needs than other families. We also expect that families with small children would face greater time pressures and more complex household management problems than other families. While the results from the negative assessment models are consistent with all of these effects, the lack of significant findings from the food hardship and

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[7] Because of the way in which the MIMIC model is parameterized, the coefficients in the MIMIC model are directly comparable to the coefficients from the probit model for feeling worse but not directly comparable to the coefficients from the other two models.

Table 4. Multivariate Models of Other Adverse Events

	Probit model of any events	OLS model of count of events	MIMIC model
Explanatory variables			
Age	0.0030	0.0030	0.0031
	(0.0081)	(0.0103)	(0.0043)
Male	-0.0796	-0.0002	0.0569
	(0.1723)	(0.2304)	(0.0945)
Black	-0.1082	-0.0937	-0.0259
	(0.1169)	(0.1482)	(0.0696)
Completed high school	-0.3542**	-0.3832**	-0.2017***
	(0.1282)	(0.1582)	(0.0768)
Second year of survey	0.1504	0.1237	-0.0205
	(0.1139)	(0.1453)	(0.0704)
Number of preschool age children	0.0708	0.0171	0.0680
	(0.0992)	(0.1198)	(0.0611)
Number of school age children	0.0019	-0.0016	0.0218
	(0.0551)	(0.0697)	(0.0279)
Number of other adults	-0.0953	0.0402	-0.0528
	(0.0969)	(0.1240)	(0.0740)
Two-parent household	-0.0689	0.1203	0.1207
	(0.1217)	(0.1555)	(0.0784)
Total monthly income	-0.1029**	-0.1928***	-0.1109***
	(0.0456)	(0.0595)	(0.0315)
Income missing	-0.2689	-0.9001***	-0.3929**
	(0.2365)	(0.3015)	(0.1708)
UI earnings 13-24 months ago	0.0177**	0.0243**	0.0150***
	(0.0083)	(0.0112)	(0.0056)
FS participation in last year	0.7596**	1.6652***	0.8553***
	(0.3550)	(0.4294)	(0.2328)
FS participation 13-24 months ago	-0.0734	-0.1322	-0.1647
	(0.1749)	(0.2286)	(0.1182)
Intercept, thresholds and loadings			
Intercept	0.8826**	1.9658***	-1.3945***
	(0.3999)	(0.6033)	(0.2591)
δ_2 (fell behind in rent)			-1.5226***
			(0.3406)
δ_3 (fell behind utilities)			-1.9615***
			(0.3752)

δ_4 (went without electricity)			-2.9535**
			(1.4164)
δ_5 (went without heat)			-3.3318*
			(1.7826)
δ_6 (water cut off)			-0.2063
			(0.4264)
δ_7 (telephone cut off)			-0.8533***
			(0.2532)
δ_8 (car/truck taken away)			0.2745
			(0.3104)
δ_9 (could not get medical care)			0.2997
			(0.2226)
λ_2 (fell behind in rent)			1.1512***
			(0.2527)
λ_3 (fell behind utilities)			1.2832***
			(0.2784)
λ_4 (went without electricity)			4.6246***
			(1.4861)
λ_5 (went without heat)			6.7177***
			(2.3220)
λ_6 (water cut off)			1.4443***
			(0.3671)
λ_7 (telephone cut off)			0.8969***
			(0.1926)
λ_8 (car/truck taken away)			0.8074***
			(0.2428)
λ_9 (could not get medical care)			0.6471***
			(0.1735)
σ_ε			0.7229***
			(0.1320)
R^2; log likelihood	-384.16	0.066	-1597.47

Note: Models estimated using a survey of former food stamp families in South Carolina (Richardson et al. 2003). Estimated standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.

adverse events models suggests that time pressures and household management issues are the most likely explanations.

A similar pattern appears for the number of adults, which is estimated to have a significant positive coefficient in the MIMIC model and in the individual model for feeling more stress but an insignificant coefficient in the two other individual outcome models. The estimated coefficients for other adults are less uniform across the individual specifications than the coefficients for small children—in particular, the coefficient for other adults is very close to zero in the model for feeling worse. Besides their contribution to financial resources, which the income variables already account for, more adults would add to the time and home production resources of a household but would also add to the needs of the household, increase the complexity of managing the household, and possibly lead to more conflict. The estimates from Table 5 are consistent with these latter explanations.

The coefficient for a male respondent is negative and significant in the probit model for worrying more, negative and insignificant in the model for feeling more stress, and approximately zero in the model for feeling worse. The coefficient is negative in the MIMIC specification but falls just short of being statistically significant (p-value = .11). The results for other adults and gender point to one potential drawback of single index specifications, like the MIMIC model. A single index model may mask differences in the estimated impacts of explanatory variables across outcomes. In this case, because of the large standard errors on the coefficients, it is not clear whether the differences in the coefficient values across the individual outcome models are actually significant (e.g., the 95 percent confidence interval around the coefficient on the male gender variable is consistent with large negative impacts).

As mentioned, the three-equation system for the individual assessment outcomes includes an unrestricted set of correlation coefficients. These are all estimated to be significantly positive. The correlation in the unobserved determinants of worrying more and feeling stress is especially strong. The findings of significantly positive correlations among all of the outcomes are consistent with the single index restriction.

In the MIMIC model, the subjective assessments of worrying more and feeling more stress have significantly lower reporting thresholds than feeling worse, which suggests that these are less severe events. The MIMIC estimates also reveal that reports of worrying have less item-specific variation than reports of feeling worse and that reports of stress have less item-specific variation still.

Finally, when we compare the log likelihood values of the three-equation system and the MIMIC specification, we see that the MIMIC restrictions result in a relatively modest degradation in the fit of the model. A test of the MIMIC restrictions indicates that they would be rejected at a 10 percent confidence level but not at a 5 percent confidence level (the p-value is .08).

Table 5. Multivariate Models of Changes in Subjective Assessments of Well-Being

	Trivariate probit model			MIMIC model
	Feel worse	Worry more	More stress	
Explanatory variables				
Age	0.0149	0.0050	0.0098	0.0068
	(0.0099)	(0.0079)	(0.0080)	(0.0048)
Male	-0.0154	-0.3242*	-0.2550	-0.1858
	(0.2172)	(0.1743)	(0.1814)	(0.1159)
Black	0.0175	-0.0119	-0.0351	-0.0172
	(0.1472)	(0.1146)	(0.1129)	(0.0685)
Completed high school	-0.1854	-0.0562	-0.1781	-0.1061
	(0.1524)	(0.1193)	(0.1195)	(0.0752)
Second year of survey	0.0541	-0.1537	0.0930	0.0070
	(0.1558)	(0.1107)	(0.1115)	(0.0679)
Number of preschool age children	0.1946*	0.1532	0.1448	0.1186**
	(0.1069)	(0.0933)	(0.0914)	(0.0577)
Number of school age children	0.0497	0.0619	0.0259	0.0305
	(0.0624)	(0.0548)	(0.0545)	(0.0321)
Number of other adults	0.0038	0.1295	0.2179**	0.1203**
	(0.1048)	(0.1028)	(0.0966)	(0.0579)
Two-parent household	-0.1239	0.1462	0.0940	0.0573
	(0.1503)	(0.1194)	(0.1166)	(0.0732)
Total monthly income	-0.1889***	-0.1991***	-0.1190***	-0.1159***
	(0.0602)	(0.0463)	(0.0446)	(0.0325)
Income missing	-0.5006*	-0.6476***	-0.8226***	-0.5482***
	(0.2922)	(0.2301)	(0.2420)	(0.1704)
UI earnings 13-24 months ago	0.0038	0.0082	0.0044	0.0040
	(0.0105)	(0.0088)	(0.0089)	(0.0050)
FS participation in last year	0.3068	0.3073	0.0832	0.1520
	(0.4136)	(0.3349)	(0.3337)	(0.1962)
FS part. 13-24 months ago	-0.3485	-0.0907	0.2530	0.0567
	(0.2414)	(0.1735)	(0.1726)	(0.1074)
Intercept, thresholds and loadings				
Intercept	-0.9082*	0.3896	-0.2907	-1.3009***
	(0.4762)	(0.3784)	(0.3754)	(0.2402)
ρ_{12}, ρ_{13}, ρ_{23}	0.2942***	0.5274***	0.6784***	
	(0.0849)	(0.0744)	(0.0423)	
δ_2 (worry more about family)				-2.4349***
				(0.5073)

δ_3 (feel more stress)		-4.0972**
		(1.7842)
λ_2 (worry more about family)		1.7554***
		(0.4100)
λ_3 (feel more stress)		3.2874**
		(1.4402)
σ_ε		0.6117***
		(0.1011)
log likelihood	-1015.83	-1035.47

Note: Models estimated using a survey of former food stamp families in South Carolina (Richardson et al. 2003). Estimated standard errors appear in parentheses.
* Significant at .10 level. ** Significant at .05 level. *** Significant at .01 level.